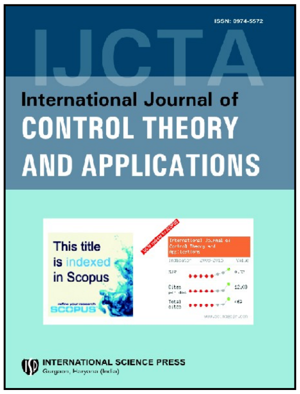

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An Automated Diagnosis of Magnetic Resonance Images for Brain Tumor using Stationary Wavelet based SFTA Texture Features

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Abstract: MRI tumor detection is very tedious in today's image processing domain. We proposed a model using a combination of SW decomposition and SFTA features. In this model have four steps such as (i) pre-processing, (ii) image enhancement, (iii) stationary wavelet image decomposition, and (iv) To extract texture features from decomposed image by using SFTA (Segmentation based Fractal Texture Analysis). The first phase pre-processing is getting MRI brain image as an input which is converted into 2D gray scale image. In second phase, adjust the image contrast to increase the brightness of an image. In next phase, the enhanced image is decomposed using 2- Dimensional Stationary Wavelet Transform. Then the SFTA texture features are extracting from the SWT low frequency decomposed image. Finally, these texture features are taken as an input to Naïve Bayes classifier which is applied for classify the MRI brain images into normal and abnormal stages depends upon the feature points. Naïve Bayes detection is a well-known for prediction and it is proven by many authors.

Keywords: Magnetic Resonance imaging, Stationary Wavelet Transform, Segmentation based Fractal Texture Analysis, Texture feature extraction, Naive Bayes classifier.

1. INTRODUCTION

Brain tumor is an abnormal cell in a brain such as neoplasm which can be varied from normal cells. MRI (Magnetic Resonance Imaging) is the most effective one to diagnose a brain tumor compare with other imaging techniques. Generally, MRI produces images that can give the difference between healthy and unhealthy tissues. MRI machines can generate different tissue contrast images due to its varying excitation and repetition time [1].

A MRI brain scan generates high resolution image which is safe and painless test that applies magnetic field and radio wave pulse to create fact images of the brain and the nearby tissues [2]. It provides better visualization of soft tissue in human body and therefore MRI modality has more influence to diagnose an enormous amount of potential tissues in many different parts of the body [3].

Primarily MRI modalities are called in terms of T1-weighted (T1-w), T2-weighted (T2-w), T1-wc (T1-weighted contrast) and FLAIR MR Images.

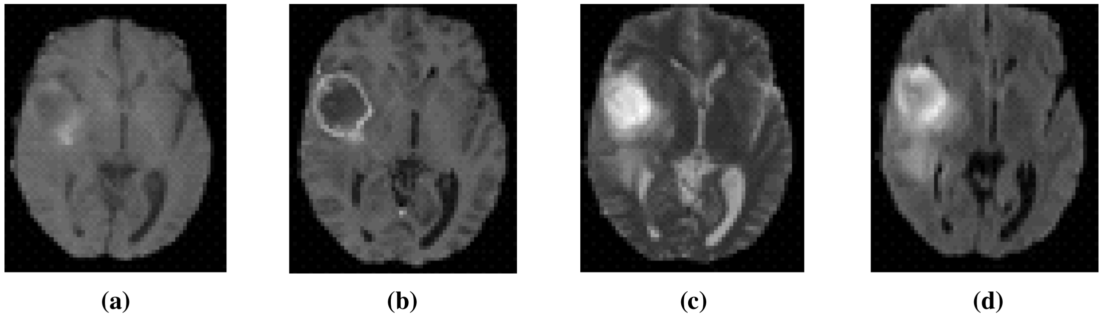


Figure 1: (a) T1-w (b) T1- wc (c) T2-w and (d) FLAIR MRI tumor images are collected from the dataset BRATS 2012 [4]

MRI brain image also can be drawn in different orientations, such as axial, coronal and sagittal are shown at below Figure 2.

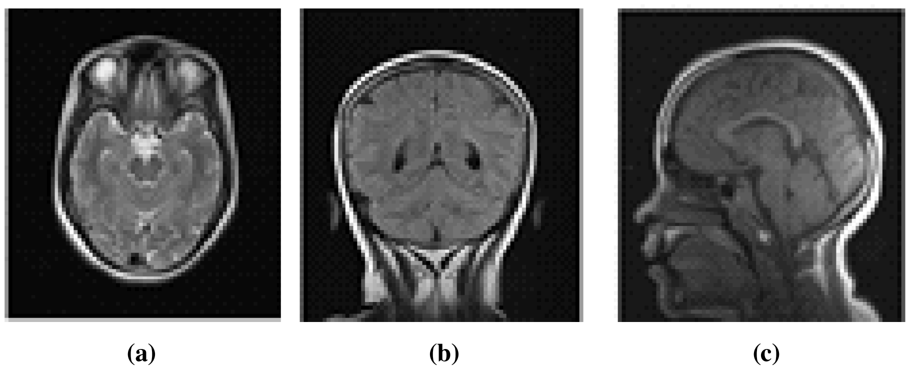


Figure 2: Types of MRI Orientation (A) Axial (B) Coronal and (C) Sagittal [2]

2. RELATED WORKS

Wavelet Transform gives better localization in together spectral and spatial domains [5]. Although, DWT (Discrete Wavelet Transform) is translation variant, that is wavelet coefficients work unpredictable one under the input signal translation [6]. The lack of wavelet coefficients translation-invariant of DWT is overcome by using Stationary Wavelet Transform (SWT) [7].

Texture analysis has three primary issues, namely texture classification, shape recovery from texture, texture segmentation [8]. In order to accurately represent the textural attributes of an image, texture analysis methods apply filter banks or GLCMs (co-occurrence gray level matrices) have to examine multiple orientations and scales. The computational cost overhead may be heavy for applying this method. SFTA performs much faster in terms of feature extraction, when matched with other methods like Gabor and Haralick [9]. Box counting algorithm is efficient one to compute the fractal dimension in linear time [10] is used in SFTA. Otsu's method gives a better thresholds selection for real world images [11]. The Otsu's method is good choice for applications that demand real time performance and hardware implementation [12].

3. PROPOSED SYSTEM

The proposed method is consist of following phases, which are,

1. Pre-processing
2. Image enhancement

3. Wavelet decomposition
4. Texture feature extraction and
5. MRI brain image classification using Naïve Bayes classifier.

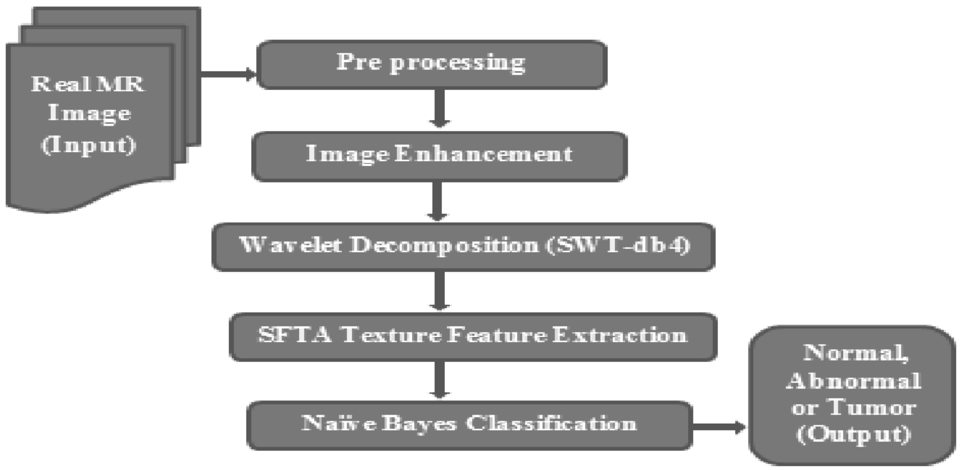
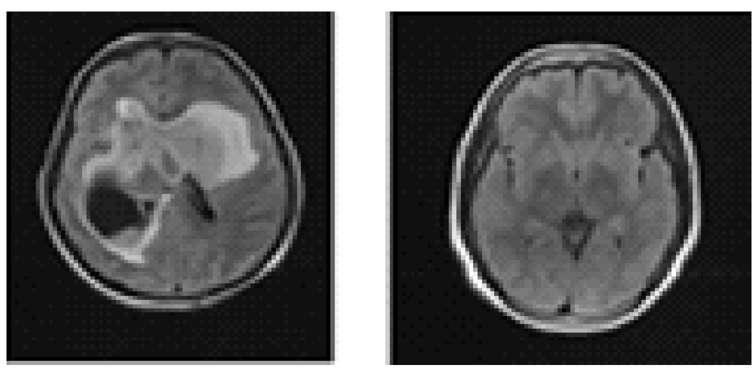


Figure 3: Proposed model of Brain Image Classification Process using novel texture feature extraction

3.1. Pre-processing

Magnetic Resonance images were collected from the patients of Tirunelveli Government Medical hospital, Tamil Nadu and BRANIX dataset [13]. These input real Magnetic Resonance images are classified into two different classes with each as normal and abnormal are shown at Figure 4. (a) and (b) respectively. These input MR images are converted to gray scale image, it holds significant intensity information.



(a) **(b)**

Figure 4: (a) Normal and (b) Abnormal brain images

The range of intensity value may be at 0 to 255. Then the output of gray scale image is produced which is created exclusively of shades of gray.

3.2. Image enhancement

The converted gray scale image is given as an input to image enhancement process. Here contrast adjustment is done in an image to increase the brightness. Means, if there is no sharp distinct between black and white pixels contrast enhancement is applied. It gives more prominent edges and sharpened image and also increase the overall quality of an image. This contrast enhancement is used for visualization purpose.

3.3. Wavelet Decomposition

Enhanced input MR image is decomposed into different frequency image by using 2D SWT. SWT decomposition is the process of using two appropriate filters (high pass and low pass) at each decomposition level.

$$A_{x,\,l+1}(i,j) = \Sigma_{k,m}\, h_k^l\, h_m^l\, A_{x,l}\,(i+k, j+m) \tag{1}$$

$$D^v_{x,\,l+1}(i,j) = \Sigma_{k,m}\, g_k^l\, h_m^l\, A_{x,l}\,(i+k, j+m) \tag{2}$$

$$D^h_{x,l+1}\,(i,j) = \Sigma_{k,m}\, h_k^l\, g_m^l\, A_{x,l}\,(i+k, j+m) \tag{3}$$

$$D^d_{x,\,l+1}\,(i,j) = \Sigma_{k,m}\, g_k^l\, g_m^l\, A_{x,l}\,(i+k, j+m) \tag{4}$$

These filters are dilated recursively such as at scale 2^l, 2^{l-1} zeros are appended between their coefficients [14]. Decomposition of SWT is shown in below Figure 5.

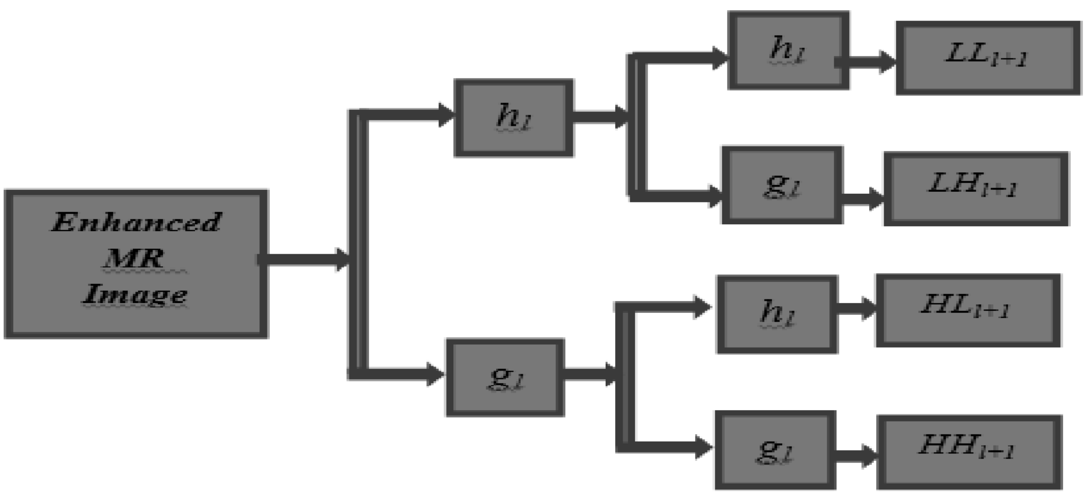


Figure 5: 2D- SWT decomposition.LL_{l+1} ($A_{x,\,l+1}$) constitutes the approximate image. LH_{l+1} ($D^h_{x,\,l+1}$), HL_{l+1} ($D^v_{x,\,l+1}$), and HH_{l+1} ($D^d_{x,\,l+1}$) constitute the details of an image

To calculate the level l+1 from the l, the following equations must be used [15]. Where (i, j) is a pixel position, $A_{x,\,l}$ is an image approximation at scale 2^l. SWT image decomposition at scale 2^l results in one approximation of original image $A_{x,l}$ low-frequency, in addition to three high-frequency image details along with horizontal ($D^h_{x,l}$), vertical ($D^v_{x,l}$) , and diagonal ($D^d_{x,l}$) directions.

3.4. Texture Feature Extraction

Texture analysis forms distinction of normal and abnormal tissue easy. The proposed system uses the SFTA texture features. SFTA is a powerful method together describes the segmented texture patterns and extracts the characteristic of MR brain image which results are feature vector.

The SFTA consist of two important part as

(i) The Two Threshold Binary Decomposition (TTBD)

(ii) SFTA feature extraction part.

3.4.1. Two Threshold Binary Decomposition

In TTBD, SWT decomposed low level frequency brain image $I_g(x, y)$ is taking as an input and it gives set of binary image. The very earlier step is to calculate the threshold set T for an each decomposed brain image. Threshold set T has been represented as $T = \{t(1), t(2), \ldots, t(n)\}$. where n is the total number of threshold values in threshold set(T) and it is desired by the user.

In single threshold binary decomposition, image $I_g(x, y)$ is converted into binary image $I_b(x, y)$ by using successive threshold operations as follows,

$$I_b(x, y) = \begin{cases} 1, & if\ I_g(x, y) \geq t \\ 0, & otherwise \end{cases} \tag{5}$$

Similarly, TTBD incorporates the results of input gray level distribution to calculates the thresholds set as described in Otsu algorithm[11]. That is accomplished by selecting pairs of thresholds as follows.

$$I_b(x, y) = \begin{cases} 1, & if\ t_l < I_g(x, y) \leq t_u \\ 0, & otherwise \end{cases} \tag{6}$$

Where $I_b(x, y)$, $I_g(x, y)$, t_l and t_u designate binary image, input gray scale image, lower threshold and upper threshold values respectively.

3.4.2. SFTA Feature Extraction

The SFTA texture feature vector is expressed by the mean gray level, size and boundaries fractal dimension of each resulting binary images. Here the fractal measurements of binary images are describe the boundary complexity of objects and structures segmented in an input image. SFTA texture algorithm has been shown in below Figure 6.

Impose: decomposedGrayscale image I_g and no. of thresholds n_t.
Confirm: *Texture* Feature vectorV_{SFTA}.
begin
i. $T \leftarrow$ multilevelOtsu(I_g, n_t)
ii. $T_A \leftarrow \{\{t_i, t_{i+1}\} : t_i, t_{i+1} \in [1..|T|-1]\}$
iii. $T_B \leftarrow \{\{t_i, n_l\} : t_{i \in T,\ i \in [1..|T|]}\}$
iv. $i \leftarrow 0$
v. for $\{\{t_l, t_u\} : \{t_l, t_u\} \in T_A \cup T_B\}$ do
vi. $I_b \leftarrow$ twothresholdSegmentation(I_g, t_l, t_u)
vii. $\Delta(x, y) \leftarrow$ findBorders(I_b)
viii. $V_{SFTA}[i] \leftarrow$ boxCounting(?)
ix. $V_{SFTA}[i+1] \leftarrow$ meanGrayLevel(I, I_b)
x. $V_{SFTA}[i+2] \leftarrow$ pixelCount(I_b)
xi. $i \leftarrow i+3$
xii. end for
return V_{SFTA}
end

Figure 6: Texture feature extraction algorithm

If the size of feature vector (n_t) is 12, total number of obtained binary images are 24, in which each image gives 3 features such as size, mean gray level and boundaries of fractal dimension. Therefore , the total number of features in decomposed MR brain image are 72 features.

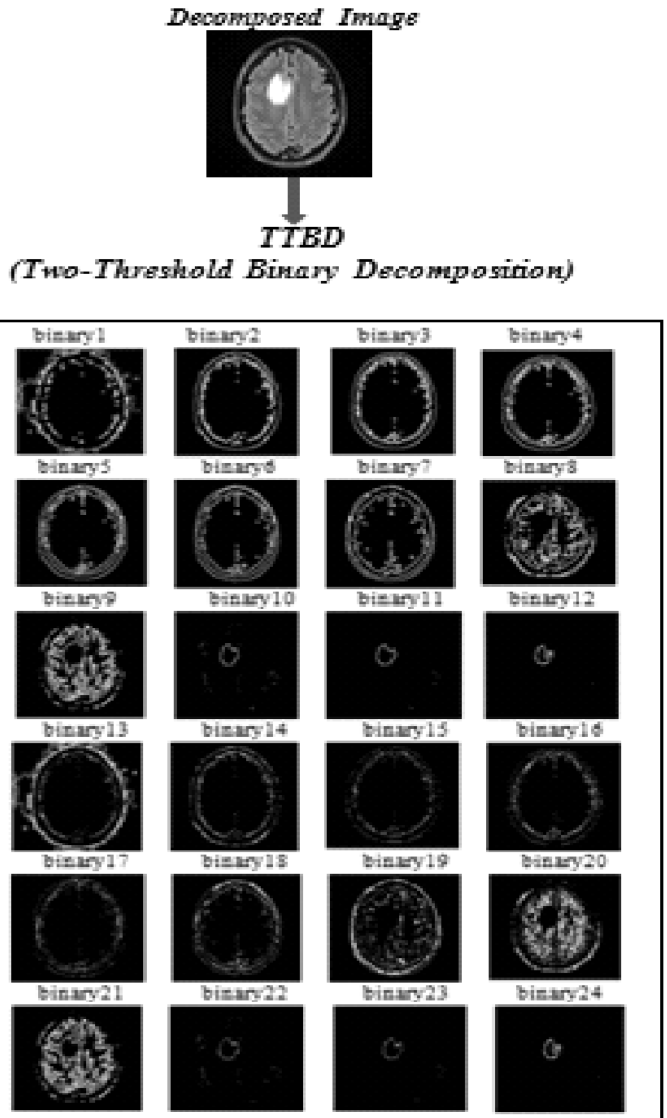


Figure 7: The End results of two threshold binary image decomposition

3.5. MRI brain image Classification

Naïve Bayes classification is one of the supervised learning algorithms, which is used to recognize the normal and abnormal brain images. The testing object has classified depends on the training samples and these texture features.

4. RESULT AND DISCUSSION

The outcome of classification has been presented as statistical measures such as Confusion Matrix, Accuracy. Table 1 illustrates the confusion matrix of a system that permits to classify the two classes 1 and 0. Here that predicted attribute, 1 means normal and 0 means abnormal.

Table 1
Confusion matrix for performance evaluation

	Predicted Class	
Class	*1*	*0*
1	TP (True Positive)	FN (False Negative)
0	FP (False Positive)	TN (True Negative)

Testing set has been composed of 38 normal and 45 abnormal images, totally 83 images. The below table describe the confusion matrix of testing images.

Table 2
Confusion matrix for tested images

N=83	*Predicted Normal*	*Predicted Abnormal*
Actual Normal	28	10
Actual Abnormal	13	32

Accuracy of Naïve Bayes classifier has been computed, using below equations,

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP + FN} * 100 \quad \textbf{(7)}$$

5. CONCLUSION

In this paper, experimentally proved that SW decomposition based SFTA system predict and classifies the normal and abnormal class with good accuracy level above 72% for a minimal amount of MRI training images. This system tested with 83 MRI brain tumor and non-tumor images. The future work will lead to use neural network for training and prediction. The purpose of using neural networks is to optimize the training and improve the system accuracy to the best rates.

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